MULTIMODAL IMAGE FUSION TECHNIQUES FOR BRAIN TUMOR DETECTION USING EFFECTIVE SEGMENTATION AND CLASSIFICATION ALGORITHMS

A SYNOPSIS

Submitted by

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1. INTRODUCTION

Multimodal image fusion has become a hotspot in the field of medical technology in recent years. A single medical device can only obtain single modal images, which results in limited information. Doctors often need an abundant number of multimodal images to obtain comprehensive information to diagnose illness. When multimodal images are used directly, the disease diagnosis workload will increase greatly, and interference and misjudgments will easily occur. Extensive information in multimodal images can be very well integrated through fusion algorithms, which have been widely used in the medical field. The aim of medical image fusion is to improve the clinical diagnosis accuracy, so the fused image is generated by preserving salient features and details of the source images. The implementation of multimodal medical image fusion is using the spatial domain or in transform domain. In spatial domain, corresponding spatial pixels from images like CT or MRI combine (Zhuet al, 2020), by means of fusion rules. However, the quality of the fused images is low, due to poor edge and contour detection and blurring. This is the main drawback with spatial domain. In general, edge and contour representation are vital analysis medical images as they characterize the tumor size or outline of the tumor

Multimodal medical image fusion is the process of merging multiple images captured by multiple sensors by extracting and integrating the complementary information of the source images being fused. The fused image can provide better interpretation and further can increase the diagnostic accuracy and clinical applicability. For example, the fusion of the complementary anatomical information provided by CT and MR modalities results in more localized and factual clinical interpretations. Similarly, fusing the anatomical and functional modality images can lead to a more comprehensive representation and provide better demarcation among the benign and malignant tissues (Dogra et al, 2017). Hence, multimodal medical image fusion can be regarded as a high-value tool for clinicians and radiologists to infer the causes of different neurological anomalies and may assist them to come up with a more accurate and reliable diagnosis, especially in critical neurological diseases. The inferences of the above discussion have motivated us to develop different fusion frameworks to fuse anatomical to anatomical and anatomical to functional images to provide an efficient and accurate diagnosis

The common practice of image fusion utilizes image registration (Schnabel et al, 2016), dealing with alignment of data from various multimodal or time-framed images, and image

segmentation that deals with the description and determination of pertinent items in 2D and 3D visual-data images. Hence, image fusion obtains an improved and enhanced output image from the input images. Thus, the key purpose behind image fusion is to create usefully informative and classifiable images that can be put to numerous beneficial utilizations. The main goal of the research method is to improve the accuracy of image fusion using effective algorithms. This work starts with the exposure of overall pipeline with Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) brain image classification algorithm with optimization based feature selection methods. The next section summarizes the literature review on segmentation, feature extraction, feature selection and classification algorithm with their limitation along with the different contributions

2. LITERATURE SURVEY

[4] Pritika and SumitBudhiraja (2016) discussed about the multimodal image fusion which plays a pivotal role in medical field by fusing the complementary information of different modalities like CT and MRI into a single image. In this work, an image fusion scheme based on the guided filtered multi-scale decomposition is proposed. First, the source images are decomposed into a base layer and series of detail layers by using guided filter. Then, different fusion rules are employed for fusing the base layer and detail layers. Simulation results show that the fusion technique performs better than the traditional techniques in preserving salient features in the fused image without producing distortion

[5] Guo, Lingling., et al (2020) suggested multi-feature extraction technique based on PCA which is used for nonlinear dynamic process monitoring. The method integrates dynamic inner PCA (DiPCA), PCA and Kernel PCA (KPCA) methods through a serial structure to extract the dynamic, linear and nonlinear features among the process data. Along with the method, the original data space is decomposed into several orthogonal subspaces, in which abnormal variations of different features can be monitored. The results are carried out to demonstrate the superior process monitoring performance of the PCA method compared with other relevant methods

[6] Alam, MdShahariar., et al (2019) introduced the template-based K-means algorithm, in which updated memberships were determined by distances from the cluster centroid and the cluster data points using the Fuzzy C-Means (FCM) algorithm; and improved FCM clustering were used for detecting tumors using CT scans. The approach improved the identification of damaged and

normal brain tissues, as demonstrated by simulation results, while sacrificing just a small amount of grayscale intensity. Moreover, our method can identify human brain tumors in seconds, when earlier algorithms took minutes

[7] Yan, Chenggang., et al (2020) introduces Multi-view approaches may effectively maintain the varied properties of data, noted. The study's advancements on learning through hashes provided multi-view deep neural networks for retrievals that were effective, innovative, and greatly enhanced retrieval performances. The study's supervised multi-view hash models showed improvements in multi-view information utilising neural networks. Their novel hash learning combined deep and multi-view learning. The use of stability evaluations actively analyzed links between views that impacted network optimizations. The benefits of both convolution and multi-views were retained for explorations by multi-data fusion algorithms in hamming spaces

[8] Ma, Jiayi., et al (2020) introduced a novel end-to-end model called DDcGANs (Dual-Discriminator conditional Generative Adversarial Networks). Through this technique, a generator and two discriminators create an adversarial game. DDcGANs could constrain downscaled fused images for sharing attributes with infrared counterparts. Multi-modality medical images were merged using DDcGANs where low-resolution positron emission tomography images were used with MRIs. Qualitative and quantitative trials of DDcGANs showed the scheme's better performances in terms of both visual effects and quantitative measurements

3. PROBLEM SPECIFICATION

Image fusion aims to integrate multiple images of the same scene into an artificial image which contains more useful information than any individual one. Due to the constraints of imaging sensors and signal transmission broadband, the resolution of most source images is limited. Also, the image quality is not achieved significantly. The existing approaches has drawback with time consumption and inaccurate image results. Still the techniques have issue with earlier brain tumor detection hence it leads lower mage fusion performance. Also, multi-view image fusions have not been greatly improved. Medical image fusions are crucial elements in image based health care diagnostics or therapies, and generically applications of computer visions. However, majority of existing methods use unrealistic assumptions that source photos are noise-free, a rarity in actual usage. When pictures are distorted by noises, classical fusion techniques perform badly. Hence, fusion techniques that properly maintain information comprehensively from multiple faulty

pictures need to be created. Simultaneous reductions of noise with textural feature enhancements are challenging tasks. To overcome the above mentioned problems, in this research, effective algorithms have been proposed

4. MOTIVATION OF THE RESEARCH

The motivation of image fusion is to combine information from multiple images of the same scene into a single image that ideally contains all the important features from each of the original images. The resulting fused image will be thus more suitable for human and machine perception or for further image processing tasks. Medical image fusion is one of the most important subcategory of image fusion. Medical image fusion encompasses a broad range of techniques from image fusion and general information fusion to address medical issues reflected through images of human body, organs, and cells. Generally the multi-modal medical image fusion is the process of combining the information from each of the input medical images that taken from specific organ of the body in to a single image, this resulted image is named fused image. Fused image is more useful than any of the input medical images. Different medical images have different features, for example the origin of MRI is very powerful magnetic source and radio waves. These images can represent the details of internal body structures and give useful information about soft tissues such as heart, brain tumors, lungs and livers.

5. OBJECTIVE OF THE RESEARCH

The important goal of the proposed study is to attain effective image fusion results with better accuracy and lower execution time

1. To develop Enhanced Bat Optimization and Absolute Maximum Fusion Rule (EBO+AMFR) scheme for better image fusion performance
2. To implement Region growing based K-Means Clustering (RKMC) segmentation algorithm and Improved Convolutional Neural Network (ICNN) algorithm to increase the CT and MRI brain image fusion performance
3. To execute Enhanced Lion Swarm Optimizations (ELSO) with Ensemble Deep Learning (EDL) algorithm for multi view image fusion performance

6. CONTRIBUTION OF THE RESEARCH

1. Efficient image fusion using multi scale decomposition and absolute maximum fusion rule for MRI and CT brain images

2. Clustering based image segmentation for optimal image fusion using CT and MRI images
3. Multi view image fusion using ensemble deep learning algorithm for MRI and CT images

The overall block diagram of the proposed system is illustrated in Figure 1

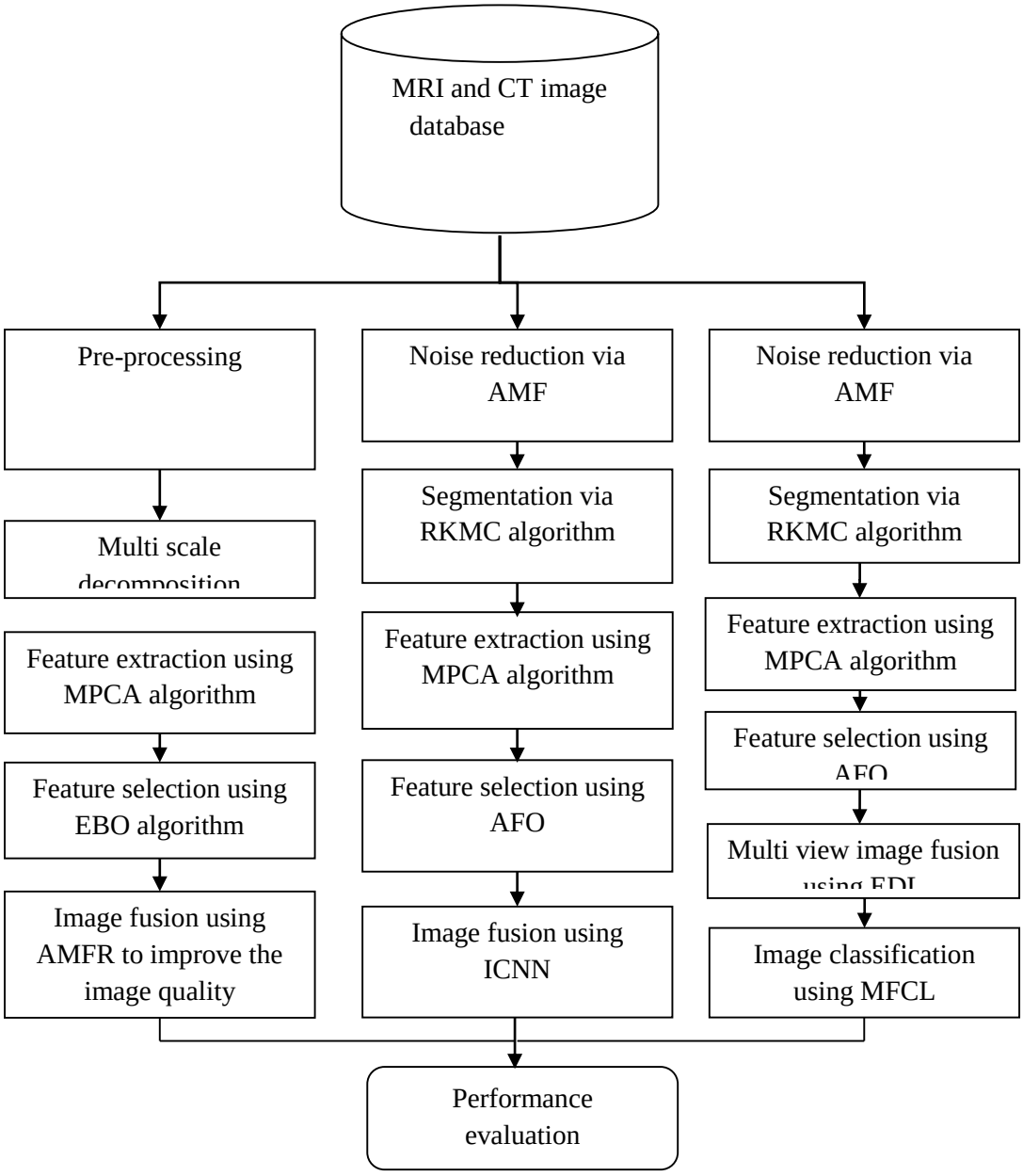
MRI and CT image database
Pre-processing
Multi scale decomposition
Feature extraction using MPCA algorithm
Feature selection using EBO algorithm
Image fusion using AMFR to improve the image quality
Noise reduction via AMF
Segmentation via RKMC algorithm
Feature extraction using MPCA algorithm
Feature selection using AFO
Image fusion using ICNN
Noise reduction via AMF
Segmentation via RKMC algorithm
Feature extraction using MPCA algorithm
Feature selection using AFO
Multi view image fusion using EDL
Image classification using MFCL
Performance evaluation

Figure 1 The overall block diagram of proposed approach for image fusion

7. PROPOSED METHODOLOGY

7.1 Efficient image fusion using multi scale decomposition and absolute maximum fusion rule for MRI and CT brain images

In the first work, Enhanced Bat Optimization and Absolute Maximum Fusion Rule (EBO+AMFR) scheme is proposed to improve the image fusion performance. This work contains main steps are such as pre-processing, decomposition, feature extraction, feature selection and image fusion process. Initially pre-processing is done for improving the image quality by removing the artefacts. Then the CT and MRI images are decomposed into low and high frequency layersusing linear filter based multi scale decomposition process. After that, feature extraction is applied through the Modified Principal Component Analysis (MPCA) which extracts the more informative image features. Then, the feature selection process is done by using EBO algorithm which selects the more relevant and important features from the given CT and MRI image database. Based on the activities of the bats, the fitness values are computed to decrease the computational complexity effectively for the given CT and MRI image dataset. It is built to perform as a crew of bats finding their prey or foods utilizing their ability of echolocation. Finally, image fusion is performed using Absolute Maximum Fusion Rule (AMFR) which merges the useful and significant image features. Fused CT and MRI brain images assist in faster detection and diagnosis of brain tumors. They provide superior results in comparison to individual CT or MRI images. From the result, it concluded that the proposed EBO+AMFR algorithm provides better performance in terms of higher accuracy, Peak Signal to Noise Ratio (PSNR) and lower Root Mean Square Error (RMSE), execution time rather than the existing algorithms

7.2 Clustering based image segmentation for optimal image fusion using CT and MRI images

In the second work, Improved Convolution Neural Networks (ICNNs) and Region growth-based K-Means Clustering (RKMC) are proposed to boost the quality of brain image fusions obtained from CT and MRI images. The primary stages of this task consist of eliminating noise, segmenting images, extracting and selecting features, and fusing images. AMFs (Adaptive Median Filters) are first used to eliminate noise from MRIs and CTSIs of the brain, improving the image quality. With the help of the RKMC algorithm, MRI and CTSI scans can be segmented into their constituent pieces, which can then be seen either as grayscale images or as pictures of objects. The

RKMC algorithm is able to adequately account for the possibility of tumors in white images. After RKMC has been applied to the database of MRI and CT images, the newly inserted pixels are inspected to ensure that they have been placed in the correct class. More useful image features can be extracted with the use of MPCAs (Modified Principal Component Analyses). To determine if the current state is abnormal or not, the PCA method is utilized to extract the concealed data, and the suggested system is then tweaked accordingly. Afterwards, features with the highest fitness values are chosen by using AFOs (Adaptive Firefly Optimizations). Image fusions of multimodal images are carried out using ICNNs, which generates the image's lower, middle, and higher-level contents. Incorporating important and relevant image characteristics from all viewpoints and perspectives improves feature training and testing. Proposed ICNNs are composed of the input, convolution, and fully linked layers. The value of the proposed method for evaluating high-dimensional data is undeniable. It employs a parameter-sharing approach to control and reduce the size of the number of parameters in convolution layers. The results show that the proposed RKMC+ICNNs outperform the state-of-the-art approaches in terms of accuracy, PSNR, RMSE, and runtime

7.3 Multi view image fusion using ensemble deep learning algorithm for MRI and CT images

In the third work, Enhanced Lion Swarm Optimizations (ELSO) with Ensemble Deep Learning (EDL) algorithm is introduced to improve the multi view image fusion performance. The primary steps in this study include image fusions, noise reduction, segmentation, feature extraction, feature selection, and picture classification. Initially noise removal is done by using AMFs (Adaptive Median Filters) for improving the image quality by removing noises in brain’s MRIs and CT images. Then the modality MRIs and CT images are segmented using RKMC algorithm and it is used for subdividing images their ingredient regions or objects. It segments the image into black and white images. RKMC algorithm considered the earlier tumor probability in the white image effectively. After that, feature extraction is applied through the MPCA (Modified Principal Component Analysis) which extracts the more informative image features. Then, ELSOs algorithm is applied for optimal feature selection which is computed by best fitness values. After that, multi view image fusions of multi modal images derive lower, middle and higher level images contents. It is done by using DCNNs (Deep Convolution Neural Networks) and TAcGANs (Tissue-Aware conditional Generative Adversarial Networks) algorithm which fuses the multi view features and

relevant image features and it is used for real time applications. It can be viewed in multiple directions and fused in the all directions which improve the training and testing features efficiently. The results of this study's ELSO+EDL algorithm implies better performances in terms of higher values of accuracies, PSNRs and lower RMSEs, MAPEs with faster executions when compared to other existing algorithms

8. RESULTS AND DISCUSSION

The image dataset is collected from https://radiopaedia.org/articles/glioblastoma.. Every picture has been scaled to 256x256 pixels. MRI and CT pictures must have complimentary information in order for them to be registered with one another. Images must be clear of noise and artefacts. CT pictures are used to identify the distinct and erratic thick border of tumor cells. The brain cells' white matter contains a hypo- or isointense mass, according to MRI scans.

The performance metrics are considered such as accuracy, RMSE, PSNR and execution time and it is evaluated using existing K-Nearest Neighbor (KNN),CNNs, PCA with Optimized Support Vector Machine (PCA+OSVM), Independent Component Analysis +Artificial Neural Network (ICA+ANN), EBO+AMFR, RKMC+ICNN and ELSO+EDL algorithms. Figure 2 shows the input CT images and MRIs. Figure 3 shows the fused image.

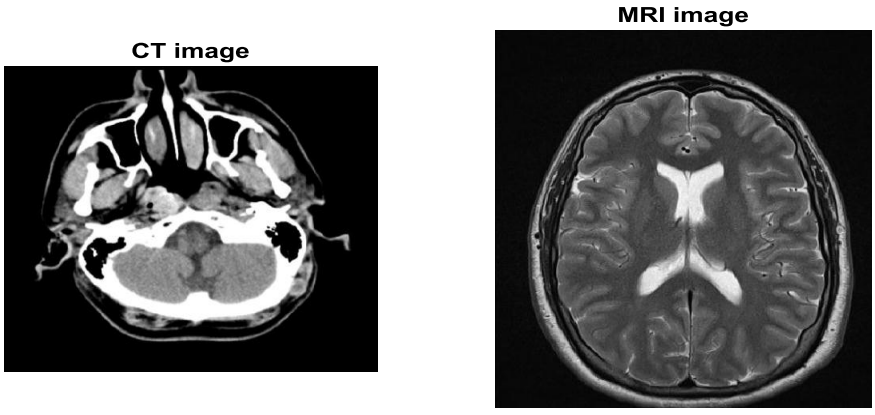

Figure 2 Input images

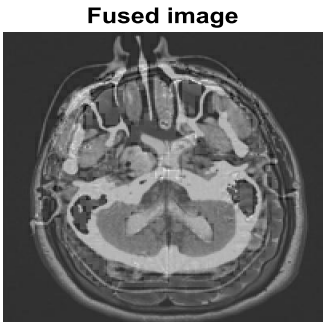

Figure 3 Fused images

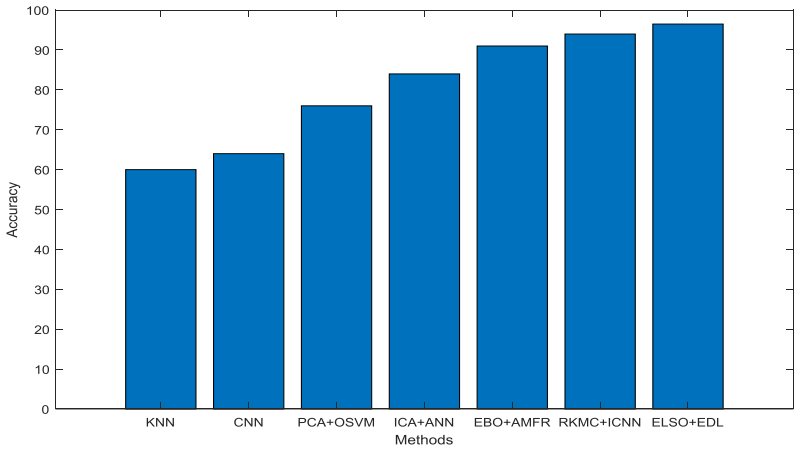

Figure 4 Accuracy

As seen in the aforementioned Figure 4, the comparison metric's accuracy is assessed using both the existing and suggested methods. For the supplied CT pictures and MRI datasets, the suggested ELSO+EDL algorithm offers greater accuracy compared to the current approaches like KNN, CNNs, PCA+OSVM, ICA+ANN, EBO+AMFR, and RKMC+ICNN. The proposed method improves the accuracies of image fusions through the EDL process

RMSEs

It is clear from the aforementioned Figure 5 that the comparative measure is assessed in terms of RMSE using current methodologies. The current KNN, CNNs, PCA+OSVM, ICA+ANN, EBO+AMFR, and RKMC+ICNN algorithms have greater MSE than the suggested ELSO+EDL technique, which offers lower RMSEs. The ensemble DCNNs and TAcGANdiminish the errors of MRIs and CTS images brain image fusions and the existence of spatial errors effectively. Thus, the result concludes that the proposed ELSO+EDL approach increases the performance of image fusions considerably.

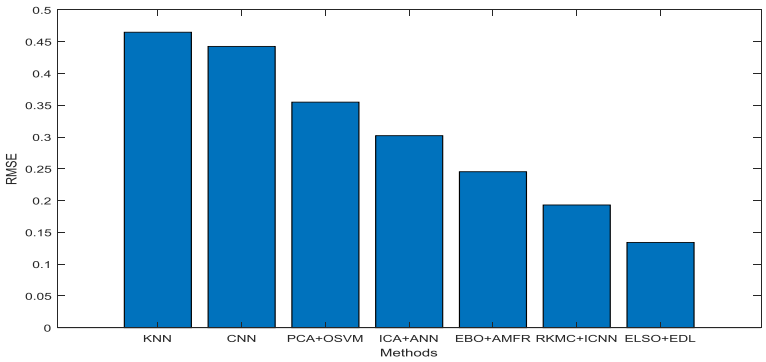

Figure 5 RMSE

PSNR

As seen in Figure 6, the comparison metric is assessed in terms of PSNR using current methodologies. The approaches form x-axis while PSNR values are plotted on the y-axis.. The current KNN, CNNs, PCA+OSVM, ICA+ANN, EBO+AMFR, and RKMC+ICNN algorithms all have lower PSNR than the suggested ELSO+EDL approach. In this study, the MFCL algorithm produces findings for picture categorization that are more precise.

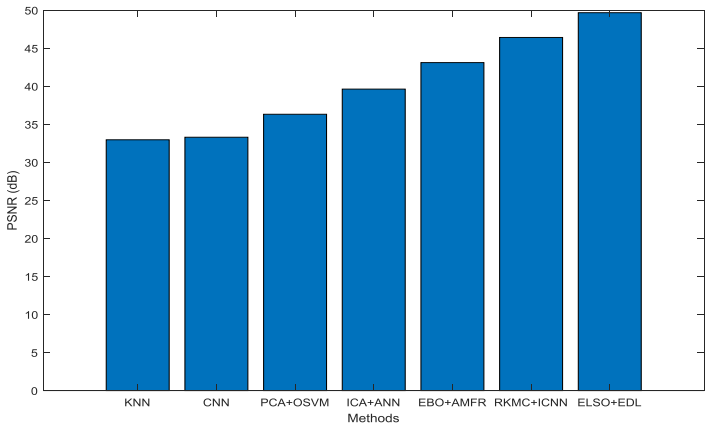

Figure 6 PSNR

Execution time

As seen in Figure 7, the comparative measure is assessed in terms of execution time using both the existing and suggested methods. The techniques are chosen for the x-axis, and the execution time value is presented on the y-axis. The ELSO+EDL technique has been presented, although the current approaches, such as KNN, CNNs, PCA+OSVM, ICA+ANN, EBO+AMFR,

and RKMC+ICNN, have higher temporal complexity. In the research, the best fitness function values are used to determine the optimal features using the ELSO algorithm.

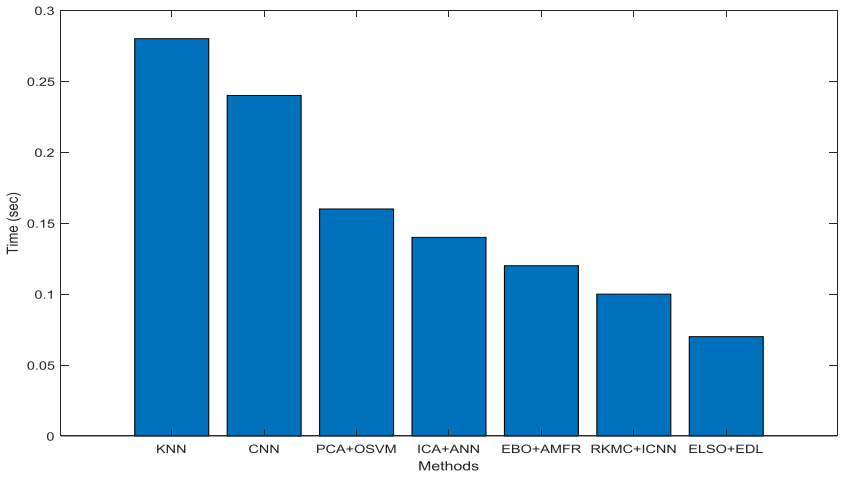

Figure 7 Execution time

Mean Absolute Percentage Error (MAPE)

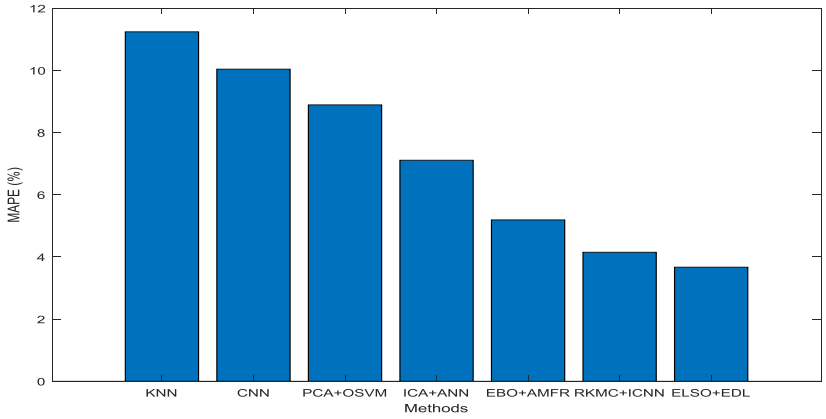

Figure 8 MAPE

It is clear from the aforementioned Figure 8 that the comparison measure is assessed in terms of MAPE using both the existing and suggested methods. The approaches form x-axis while execution times are plotted on the y-axis. The suggested ELSO+EDL algorithm offers reduced MAPE compared to current approaches as KNN, CNNs, PCA+OSVM, ICA+ANN, EBO+AMFR, and RKMC+ICNN.

Table 1 Performance Evaluation Comparison of Proposed & Existing Techniques

Methods	Performance Metrics (Average Results)				
	Accuracy (%)	RMSE	PSNR (dB)	Time (s)	MAPE
KNN	60.44	0.46022	32.604	0.28	11.494
CNN	63.964	0.44372	33.2826	0.24104	10.1
PCA+OSVM	76.258	0.35186	36.43	0.16	8.83
ICA+ANN	84.458	0.30486	39.63	0.14	7.183
EBO+AMFR	90.458	0.2417	43.04	0.12	4.93
RKMC+ICNN	93.898	0.19446	46.066	0.104	4.146
ELSO+EDL	96.5	0.1342	49.66	0.07	3.67

Table 1 shows the performance evaluation comparison of the proposed and the existing approaches. The results are evaluated for metrics as such accuracy, RMSE, PSNR, time and MAPE. It is clearly observed from the Table that the proposed ELSO+EDL approach clearly outperforms the other approaches. The proposed ELSO+EDL approach provides 96.5% accuracy and 0.1342 RMSE value. The PSNR obtained by the proposed ELSO+EDL is 49.66 with minimal time period of 0.07 seconds.

9. CONCLUSION

In the first work, EBO+AMFR algorithm is proposed to improve the image fusion performance for the given CT and MRI images. This work contains four main modules such as pre-processing, decomposition, feature extraction, feature selection and image fusion. Pre-processing is focused to improve the image quality and then CT and MRI images are decomposed. Multi-scale decomposition is focused to reduce the artifacts from the given images effectively. The feature extraction is done by using MPCA algorithm which extracts the more informative features efficiently. The feature selection is done by using EBO algorithm which is used to select the local optimal features from the CT and MRI image database. Then the image fusion is performed by using AMFR algorithm which fuses the useful and relevant image features which is used for real time applications. From the experimental result, it concludes that the proposed EBO+AMFR algorithm provides higher accuracy, PSNR and minimum RMSE, execution time than the existing ANN and KNN methods

In the second work, the RKMC+ICNN algorithm is suggested to enhance the performance of image fusion for the provided MRI and CTSIs. Noise removal, segmentation, feature extraction, feature selection, and picture fusion are some of the five primary modules of this work. The AMF algorithm, which is designed to enhance image quality, removes noise. The RKMC algorithm is

then used to segment MRI and CT brain pictures. The brain tumor is recognized in both of the black and white images that are segmented for earlier prediction. The MPCA method is used for feature extraction because it efficiently extracts the more informative characteristics. Following that, the local optimal features are chosen from the CT and MRI image database using the AFO method. It is used to aggregate pertinent data from the given modality database and remove the unnecessary characteristics as efficiently as possible. Finally, the ICNN algorithm is utilized to combine the valuable and pertinent picture features needed for real-time applications. The experimental results showed that the suggested RKMC+ICNN method outperforms the existing techniques in terms of accuracy, PSNR, and execution time. In the future, a more accurate segmentation algorithm with deep learning and a faster post-processing optimized method will be considered to further improve the performance of multimodal medical image fusion

In the third work, the ELSO+EDL method is suggested to enhance image fusion capabilities for the provided MRI and CT images. Initially, the AMFs algorithm, which is designed to enhance picture quality, does noise reduction. The RKMC algorithm is then used to segment brain pictures from MRIs and CT scans. The MPCA method is used for feature extraction because it effectively extracts the more informative characteristics. Following that, the local optimum features are chosen from the CT images and MRI image database using the ELSOs algorithm. The EDL technique is then used to combine the relevant and usable picture characteristics, which is utilised to enhance the performance of multi view images. MFCL, which predicts more precise characteristics, is utilised to classify images. It is determined from the testing results that the suggested ESLO+EDL method gives higher values in terms of accuracies, PSNRs and lower RMSEs, MAPE, execution time rather than the existing algorithms

Future work

In future work, with the advent of powerful deep learning architectures, integrated image registration, fusion, and segmentation models can be developed to further ease its applicability and usability by clinicians. Currently, most of the multimodal neurological image fusion approaches are tested on images covering a wide variety of neurological disorders. However, each disorder affects the anatomy and physiology of the brain tissue in a specific way. It would be interesting to explore, develop and examine the fusion methods specialized for performing disease specific fusion considering the characteristic information of the source images depicting disease specific structures and textures

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